FINAL REPORT

A3G Public Conversation Model:
Analyzing the Distributions of Influential and Susceptible Members in a Multi-agent Model of Text-based Online Communities

Grace Ko and Hadijat Oke
Spring 2025

1 Introduction

Persuasion and influence have been central to human interaction for millennia, shaping decisions, forging alliances, and driving societal change. The study of persuasion dates back to ancient Greece, where rhetoric was essential for civic engagement and democratic deliberation (Radakovic, 2010). Persuasion is a change in a person's belief after receiving a message from someone else. Influence is a person's ability to have others change their beliefs and be persuaded. In our experiment, we defined influence as the ability to persuade. These dynamics are not limited to face-to-face communication; they extend into the digital world, where people continue to persuade and influence one another through online interactions. As the internet has become increasingly integrated into everyday life, influence has taken new forms, emerging through posts, shares, comments, and digital engagement. Individuals use the internet primarily to interact with people they do not know or to establish new relationships. In addition, anonymous activities online involve maintaining an ongoing virtual identity (Guadagno, *et al.,* 2007).

A primary medium for modern influence is online communities. Online communities are groups of users who interact regularly around shared interests or topics, often through structured platforms that support user-generated content like posts and comments. These communities vary widely in structure and tone. For instance, Instagram emphasizes visual content paired with short captions and comments, while Reddit focuses on text-based discussion threads organized by topic. The proliferation of online communities has transformed how people connect, communicate, and exert influence. These communities serve as hubs for discussion, knowledge exchange, and social bonding, playing an increasingly important role in shaping public discourse and collective behavior.

We wanted to design a model that explores how influence spreads through an online blog community. We developed a model to understand how members influence each other and the magnitude to which different member types influence. A3G is a multi-agent model previously designed to emulate one-to-one conversations in online communities. In our investigation, we developed the A3G model to include functions to emulate an online blog community. The one-to-one conversation model is referred to as the private conversation model, and the online blog community is referred to as the public conversation model. In order to get a fulfilling representation of an online blog community, several adjustments were made to the A3G model. Instead of having one-to-one conversations, we created the public model to have a post-comment structure. A post is the starting point for online communities and blogs. A post serves as a way for a member to start a discussion in their respective community. Once a post is available in a community, members can either comment under it or make their post. We also changed the primary cycle of the experiment to create the following sequence for members in the community: they first choose to post or comment, then select a post or comment to comment under, and lastly, they generate content for the post or comment. We also removed the feature of having one-hop neighbors and changed the experiment sequence. Influence score measurements were also adjusted to be spread evenly to the author of specific posts and comments.

In our online blog community, we defined influence as the ability to change another member's stance. Members who had high influence could change the stance of many members at high magnitudes. Regarding susceptibility, we defined this metric as the number of times a member changed their stance. A member who has changed their stance five times in one conversation would be defined as more susceptible than a member who changed their stance once in one conversation. Along with our definitions of influence and susceptibility, we also explored the distributions of these measurements as we collected our results. In our paper, we analyze the probability metrics for influence and susceptibility to determine the likelihood that a member is more influential or susceptible than others.

The contributions of this paper include the following:

- A metric for quantifying influence and modeling the probability distribution of members' influence within a blog-style online community.
- A metric for quantifying susceptibility and modeling the probability distribution of members' susceptibility to influence in a blog-style online community.
- A comparative analysis of influence and susceptibility between a non-blog (one-to-one dialogue) model and a blog-based community model.

In our paper, we discuss the basis of our experiment and introduce our modifications to the A3G model to emulate an online community blog in this section, the *Introduction*. In our Background Research, we discuss research about influence in online social communities and how influence is measured in online communities. Our *Methods* section discusses how we modified the original A3G model to incorporate techniques to model an online community blog. Our *Results* discuss the metrics we use to define influence and susceptibility. It also discusses the measurements received for the members in two experiments and how likely they are to be the most influential or susceptible. These results are then compared to the original A3G model to see if there are differences between the metrics of the online community blog model and the one-to-one conversation model. The discussion and analysis of the results are stated in our *Discussion*. We conclude with the *Limitations* of our experiment and discuss takeaways in our *Conclusion*.

2 Background and Related Work

The research literature presents different methods of analyzing, detecting, and categorizing influence and susceptibility in blog and non-blog online communities. It also examines the distribution of users with different levels of participation and the proportions of posts to comments in online communities.

In their paper, Agarwal *et al.* defined influence as being recognized by other members, novelty, activity generation, and eloquence. Recognition was defined as the number of posts that reference an initial post. They defined activity generation as the number of comments posted under a post. The original creator of that post would be influential, with many comments under their post. Along with identifying influence, the authors explored the difference between active and influential members. They described active members as those who post or comment a lot; some of their content may be identified as spam. These members should not be identified as influential since they do not add substance to the conversation. The researchers also examined the distribution of influence within the blogosphere, revealing that a small fraction of bloggers exert significant influence, while the majority have minimal impact. This observation aligns with the power-law distribution, where a few nodes (in this case, bloggers) hold most influence (Agarwal *et al.*, 2011).

Tan *et al.* proposed a multi-dimensional method for detecting influence between blog posts based on blog features, sentiment, agreement analysis, and community identity. The authors evaluated 196 blog post pairs from the U.S. political blogosphere and found that agreement between bloggers, similar sentiment on shared topics, and shared community affiliation were statistically significant indicators of influence. They concluded that analyzing only textual similarity or link structure is insufficient; instead, content and community context are crucial for accurate influence detection (Tan *et al.*, 2011).

Giovanidis *et al.* introduced a novel influence ranking method for online social networks based on a dynamic model that incorporates user activity, content diffusion, and the structural layout of social platforms. Rather than relying solely on static graph metrics, their model simulates how posts propagate through Walls and Newsfeeds, combining posting and reposting behaviors. Using this framework, they define the Ψ-score, a user-specific influence measure derived from a set of balance equations modeling content visibility. The authors show that in homogeneous cases, the Ψ-score reduces to PageRank. However, in real-world datasets like Twitter and Weibo, the Ψ-score provides a more expressive ranking by accounting for asymmetric user activity (Giovanidis *et al.,* 2021).

In non-blog communities, Xiong *et al.* estimated an individual's influence through their number and quality of friends. They also developed the concept of a community label that represents the attributes represented by most members in a community, which is another key factor to a user's influence in a community (Xiong *et al.*, 2012).

Humphrey *et al.* analyzed individuals' susceptibility on Reddit's subreddit "r/changemyview". Researchers tested the significance of various features between susceptible and non-susceptible members. They categorized susceptible original posters as ones that changed their mind on all submissions, and non-susceptible original posts as ones that never changed their mind on any submission they made. They excluded any original posters that fell in the middle group of sometimes changing and sometimes not changing their minds. It found that susceptible original posters use more hedge words than non-susceptible users, thereby showing that users who are more uncertain in their content are more susceptible than non-susceptible users. Researchers also found that original posters who never changed their minds are more analytical about their content than susceptible original posters (Humphrey *et al.*, 2019).

Williams *et al.* researched what leads to individuals' susceptibility in online communities, which are one-to-one communications, such as emails, especially in the context of scams. Susceptibility was categorized as users viewing scam messages, believing in them, and acting on them. The authors identified several traits that make one more susceptible, such as having less self-control, having lower standards, as in values and ideals for oneself, and having lower awareness and tracking of one's behavior. They also emphasized trust as a significant factor and how people must use systematic evaluation to evaluate the legitimacy of incoming information and determine if it is the truth. Those who are more willing to trust others are more susceptible. The authors state that individuals are more likely to be more susceptible to a message related to an event or piece of information readily available in their memory through recent or repeated exposure. They also mentioned how emotions play a significant factor as messages that evoke a strong emotional response are more likely to make an individual believe and act on it (Williams *et al.*, 2017).

The "90-9-1" principle, as outlined by Sun *et al.* (2014), characterizes user participation in collaborative online environments. According to this model, 90% of users are passive consumers ("Lurkers") who primarily read content, 9% contribute occasionally by editing or commenting, and only 1% are highly active contributors who regularly generate new content.

Flaugher *et al.* (2020) reported that Reddit's annual activity included approximately 303.4 million posts and 2 billion comments, yielding a post-to-comment ratio of roughly 1:6.

Our review reveals that prior studies have thoroughly characterized how influence and susceptibility manifest in blog-style communities and more discrete, one-to-one settings, detailing user roles, content distribution, and participation patterns in each. However, we did not encounter any work that directly contrasted these environments within a single experimental framework to examine how influence operates side by side in blog versus non-blog contexts.

Our work, therefore, focuses on answering three research questions:

- RQ1: How do we define and quantify the ability to influence and the susceptibility to influence in a text-based online blog community?
- RQ2: What differences exist between the distribution of the ability to influence in a text-based online blog community and one-to-one dialogue between community members?
- RQ3: What differences exist between the distribution of the susceptibility to influence in a text-based online blog community and one-to-one dialogue between community members?

3 Methods

The work in this paper is based on the existing A3G model. This model originally had functionality for only private one-to-one conversations. Members in this model discussed topics with a predefined set of members throughout the experiments. In the public conversation model, members can interact with any member's comment or post. The major modifications we made to the A3G model include adding a functionality where members could "read" existing posts and comments and then choose a post/comment to comment under. The influence score for the public conversation model was defined as the change in stance a member had when they read a post or comment. We created a graph of the dialogue among community members to represent their connections and influence on each other. We used the NetworkX Python library to compute the Centrality and Link Analysis influence measures among community members. We used these results as our basis for comparison for our Influence Score metric.

3.1 Simulating Posting and Commenting Functionality

The public conversation model simulates interactions between members through posts and comments, following the structural format illustrated in *Figure 1*. Members can create a new post or comment on an existing post or comment, building nested conversations across multiple levels.

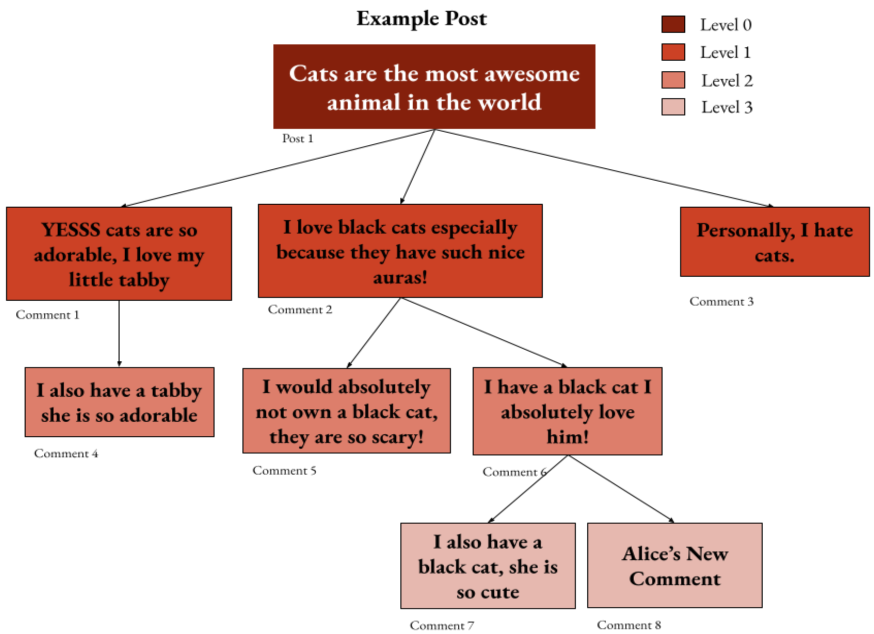

Figure 1: Diagram representing an example of a Post and the Comments under it.

To simulate these interactions, the public conversation model operates through a main loop that iterates over a predefined number of conversation turns. In each turn, the loop performs four key functions: (1) it updates each member's online or offline status, (2) it determines whether members choose to post or comment based on predefined probabilities, (3) it records each member's perspective[1] based on the content they read and produce, and (4) it updates each member's stance accordingly. *Figure* 2 provides a schematic diagram of our model that determines whether each member chooses to post or comment. This decision is governed by predefined probabilities associated with each member's type: Leader members are most active, followed by Participants, and then Lurkers. The model draws a random number for each member to determine whether the member will participate in the conversation at that conversation turn. Suppose the random number exceeds the

[1] A perspective is the last post or comment content that a member wrote in the community. In the public conversation model, each member has a perspective array that stores a predefined number of background beliefs and most recent responses that the member made.

predefined threshold value. In that case, the model draws a second random number to determine whether the member will participate in the dialogue by creating either a post or a comment.

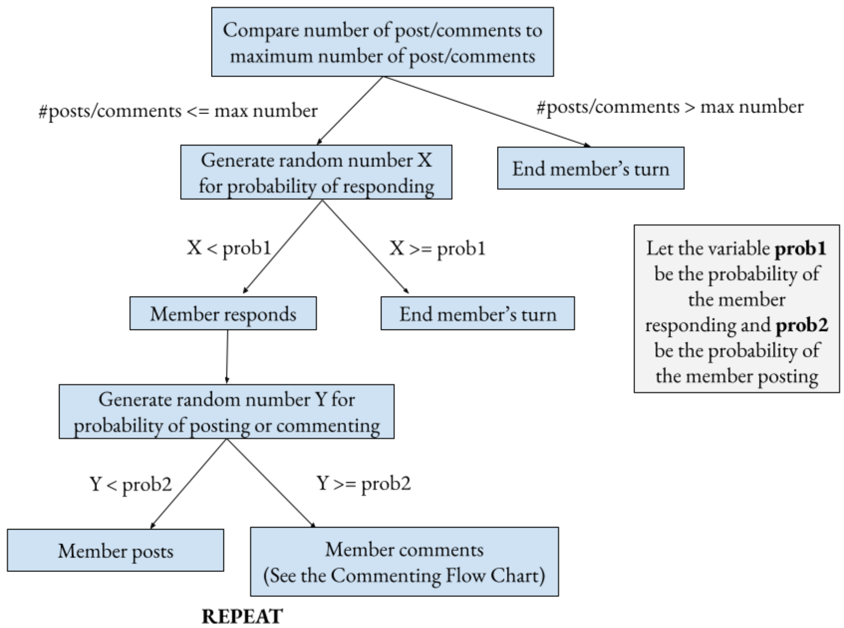

Figure 2: Diagram representing the probability of a member responding and the probability of generating either a Post or Comment.

When members decide to post or comment, they follow a decision-making process based on their assigned cognitive bias, as shown in *Figure 3*. After selecting a post, the member reads a randomized number of top-level comments. The member chooses the post or comment that best aligns with their cognitive bias and stance on the topic of discussion. If a post is selected, the member comments directly under it. If a comment is selected, the member explores the thread below the chosen comment to a randomized reading depth, identifies the most aligned comment, and replies. Each node in the dialogue graph among community members includes the member's stance, member ID, and the content of their post/comment.

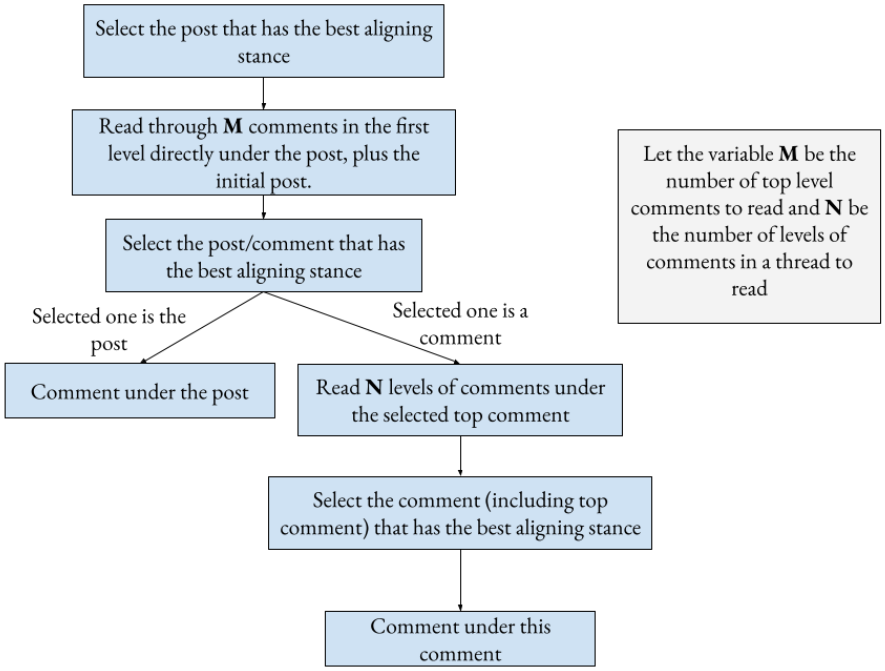

Figure 3: Diagram representing a member reading through and existing Posts and Comments, selecting one, and then commenting under it.

3.2 Defining and Measuring Influence Score in an Online Community Blog

At every conversation turn, each community member can increase or decrease their influence score based on their ability to influence other community members engaged in the dialogue. The decision to comment on another member's post or comment could change a community member's stance on the topic of discussion. That is, the member of the parent comment or post influenced the member of the post or comment. The magnitude of the member's stance change is the measure of influence exerted by the author of the parent comment or post. For example, if a member changed their stance from PRO-HIGH to CON-HIGH after reading a post/comment and writing their own, the influence score for the author of the parent comment or post would increase by 32 points.

However, in the public conversation model, influence is not attributed solely to the author of the parent comment or post. Instead, there are four scenarios in which the influence score is attributed to other members in the dialogue chain. The first scenario occurs when a member comments directly under a post. In this case, the post's author is attributed 100% of the influence (see *Figure 4*). If a member comments under a comment directly under a post (see *Figure 5*), the author of the parent is attributed 70% of the influence, and the author of the comment, 30%. Suppose at least one comment exists between the post and the parent comment. In that case, the author of the parent comment is attributed 50% of the influence, the author of the post, 20%, and the remaining 30% is distributed equally among the authors of the intervening comments (see *Figure 6 and Figure 7*). Lastly, if the member is the same as the author of the post, influence would be attributed to the authors of the parent comment and the intervening comments, not to the post's author; you cannot influence yourself.

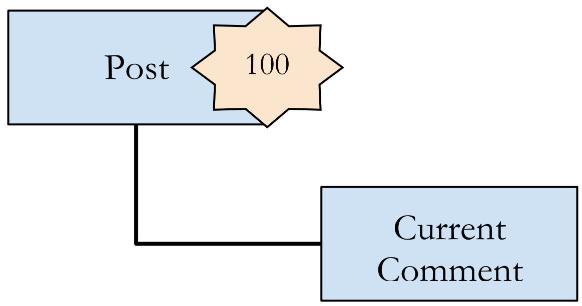

Figure 4: The current comment is directly under a post; therefore, influence is attributed to the post's author.

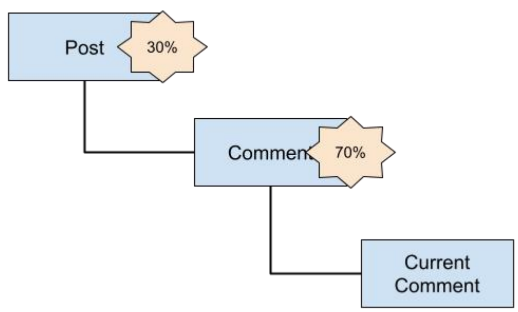

Figure 5: The current comment is under a post and a comment, so the post's author is attributed 30% of the influence, and the parent comment's author, 70%.

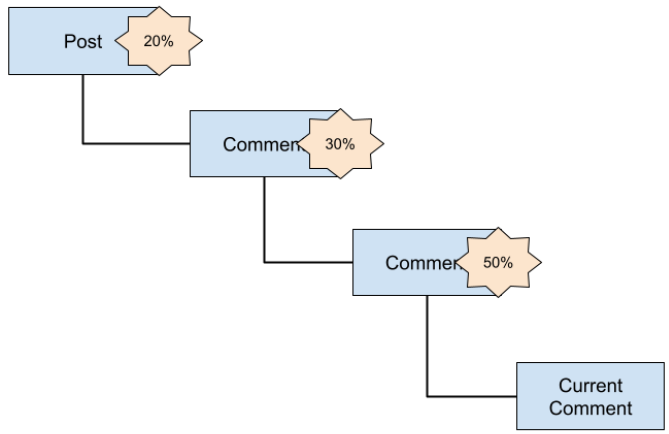

Figure 6: The current comment is under a post and two comments; therefore, the author of the parent comment is attributed 50% of the influence, the author of the intervening comment, 30%, and the post author 20%.

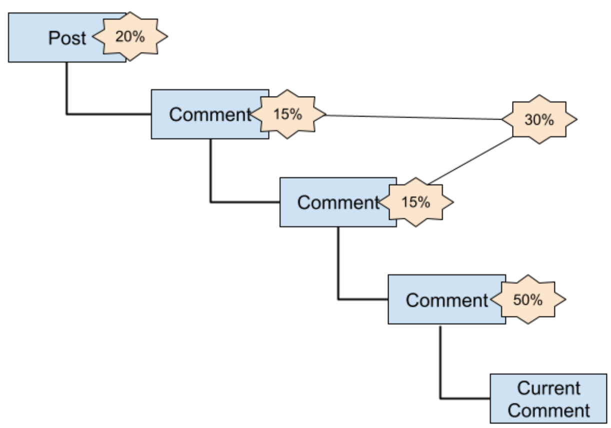

Figure 7: There are more than two comments between the current comment and the post. The post's author is attributed 20% of the influence, the authors of the intervening comments share 30%, and the author of the parent comment shares 50%.

Along with using influence score as a metric for the members in the public conversation model, we also define the susceptibility of a member to influence through the behavior of the members in the community. Members are deemed susceptible to influence based on the number of times they change their stance on the topic of discussion. For example, a member with the highest amount of stance changes throughout the experiment will be the most susceptible.

3.3 Graph Analytics

To model influence, we create a directed, dynamic graph (see *Figure 8*) to show how each member influences other members. Each node stores a member's ID, and each edge its cumulative influence score. The graph is dynamic because members are added to it each time a member first contributes a post or a comment. We used the NetworkX Python library to compute two Centrality (Betweenness and Closeness) measures, and three Link Analysis (PageRank, Authorities, and Hubs) measures.

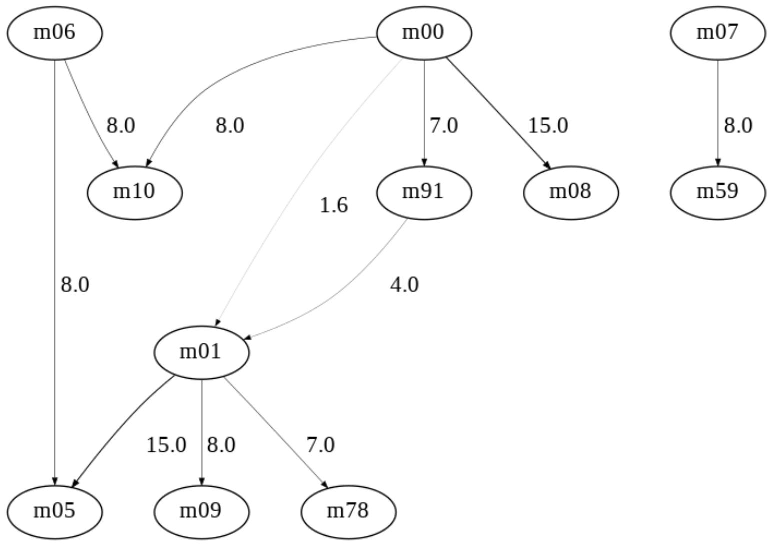

Figure 8: Example of the directed, dynamic graph representation of influence between members at the end of a conversation turn.

3.3 Creating Experiment Set-up

We defined two experiments to test the ability to influence and the susceptibility to influence in a text-based online blog community: 1) CONTROL , and 2) ACTIVE LEADER. Each experiment consists of a community with 200 members divided according to the 90:9:1 model of online community activity into 2 Leader member types, 18 Participant member types, and 180 Lurker member types (Nonnecke, 2000; Nielsen, 2006). Each member type was assigned a probability of posting or commenting to reflect their engagement level: Leaders had a 95% chance of creating a post or comment. Participants had a 15% chance, and Lurkers a 1% chance. This approach allowed us to simulate realistic behavioral dynamics in a text-based online blog community (Sun *et al.*, 2014; Agarwal, 2011). This approach allowed us to achieve a post-to-comment ratio similar to that shared in Reddit's annual reports (Flaugher *et al.*, 2020). In the CONTROL experiment, Leaders and Participants were assigned the Homophily cognitive bias, while Lurkers were assigned the Status Quo cognitive bias. In the ACTIVE

LEADER experiment, Leaders were assigned the Heterophily cognitive bias, Participants the Homophily cognitive bias, and Lurkers the Status Quo cognitive bias.

4 Results

This work investigates three research questions about influence dynamics in text-based online blog communities. The first examines how to define and quantify influence and susceptibility to influence in a text-based online blog community. The second explores whether differences exist between the distribution of the ability to influence in a text-based online blog community and one-to-one dialogue between community members. The third investigates whether differences exist between the distribution of the susceptibility to influence in a text-based online blog community and one-to-one dialogue between community members . These questions aim to formalize the mechanisms of ability to influence and susceptibility to influence within the structural and social context of text-based online blog communities.

4.1 Modeling Influence and Susceptibility in Blog Communities

RQ1: How do we define and quantify the ability to influence and the susceptibility to influence in a text-based online blog community?

We defined and quantified the ability to influence in a text-based online blog community using two complementary approaches. The first approach, raw influence scores, involves tracking each member's influence score over the course of conversation turns and recording how many times each member was identified as the most influential at the end of each experiment iteration. The second approach, graph-based network analysis, constructs a weighted, directed, dynamic graph, where nodes represent members and edges represent the cumulative influence score of a member and using Centrality and Link Analysis algorithms to capture identify the most influential community member.

The average influence score progression over conversation turns reveals that the two Leader members (c00_m00 and c00_m01) consistently maintain the highest average influence scores, with a notable increase from the first to the final conversation turn, as shown in *Figures 9 & 10*. In contrast, the influence scores of other members—primarily Participants and Lurkers—tend to decline over time, likely due to the Leaders increasingly dominating the conversation through frequent posting and commenting. In the CONTROL Experiment (*Figure 9*), the Leaders reach average influence scores of 1032 and 1035 by the end of the simulation, while Participants remain lower, ranging between 985 and 993. In the ACTIVE LEADER Experiment (*Figure 10*), the Leaders exhibit a steeper growth in influence, achieving scores of 1039 and 1046 by conversation-turn 21, with Participants slightly higher than in the control, ranging from 991 to 997. These results suggest that in the ACTIVE LEADER condition, Leaders are more assertive in shaping discourse and influencing others, whereas in the CONTROL condition, Participants contribute somewhat more to the overall distribution of influence.

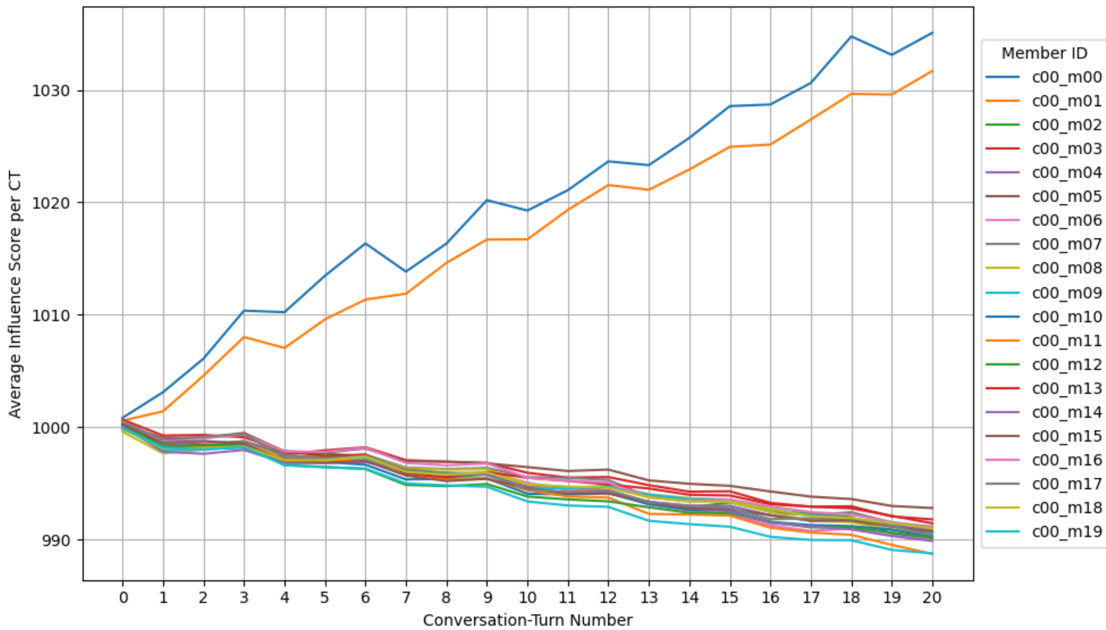

Figure 9: Corresponding progress of the Influence Scores of the non-Lurker members averaged over the iterations of the CONTROL experiment.

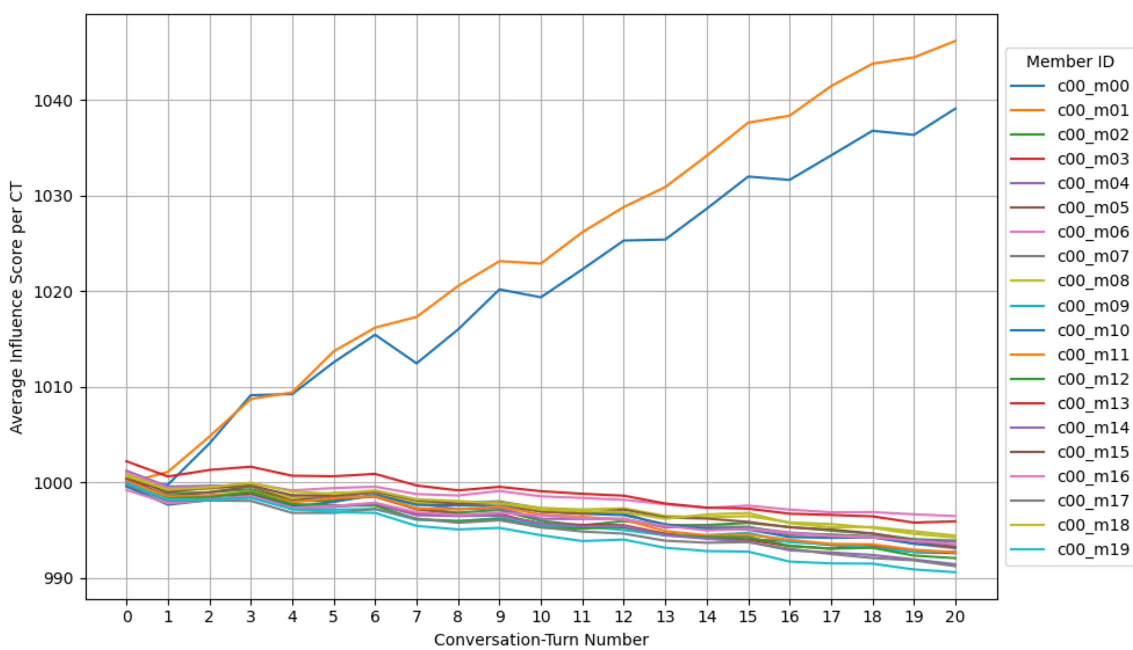

Figure 10: Corresponding progress of the Influence Scores of the non-Lurker members averaged over the iterations of the ACTIVE LEADER experiment.

The influence score was also used to determine which members were the most influential across all iterations. As seen in *Tables 1 & 2*, the most influential members, by the number of iterations they were the most influential, were the Leaders (c00_m00 and c00_m01) for both the ACTIVE LEADER and CONTROL experiment. Both experiments have the Leaders reaching at least 41 iterations where they are the most influential while the Participant members have between 0-5 iterations, and the rest of the members have 0 iterations.

Table 1: Most Influential Members by Number of Iterations for the CONTROL Experiment.

Member ID	Member Type	Iterations Identified as Most Influential
m00	Leader	48
m01	Leader	41
m13	Participant	3
m10	Participant	3
m14	Participant	2
m08	Participant	1
m05	Participant	1
m09	Participant	1
m17	Participant	1
m02	Participant	1
m03	Participant	1
m18	Participant	1

Table 2: Most Influential Members by Number of Iterations for the ACTIVE LEADER Experiment.

Member ID	Member Type	Iterations Identified as Most Influential
m00	Leader	48

Member ID	Member Type	Iterations Identified as Most Influential
m01	Leader	47
m13	Participant	5
m17	Participant	2
m02	Participant	2
m10	Participant	2
m07	Participant	2
m16	Participant	2
m08	Participant	2
m05	Participant	1
m06	Participant	1
m04	Participant	1

Along with analyzing influence with the influence score metrics, graph measures were calculated to investigate the sharing of information and the characteristics of the members in the community. The graph analytics that we focused on include the following: in-degree centrality, out-degree centrality, Closeness centrality, Betweenness centrality, PageRank Link analysis, Hubs Link analysis, and Authorities Link analysis. After running each iteration, a NetworkX graph is created showing the connections between the members and the influence they have on each other. Each of the graph measures are calculated with the generated NetworkX graph and an associated Python library. These graph measures were calculated with all the graphs being unweighted as we wanted to understand if there is a difference between the calculated influence scores and the scores of the graph measures.

For each graph measure we wanted to identify the relevance of using the calculations to define influence. Betweenness Centrality measures how often a member lies on the shortest paths between others, indicating their role as a bridge in the network. This could potentially identify nodes that are connecting disjointed parts of a graph emphasizing the spread of information and potentially the spread of influence. Closeness Centrality evaluates how close a member is to all other members, based on the average length of the shortest paths. This could identify members that discuss topics with a lot of other members and potentially influence various members. PageRank captures a node's importance by considering both the number and the weight of incoming connections, therefore giving a representation of both influence and the graph analytics in one measure. In the graph measure analysis we also look into Hubs links analysis and Authorities link analysis. Hubs are nodes that point to many high-quality authorities, while Authorities are nodes that are frequently linked to by high-quality hubs. Together, these metrics help characterize members who serve as reliable sources of information (authorities) and those who actively engage with influential content (hubs), further enriching the structural analysis of influence within the community. Lastly, we also look into in-degree and out-degree centrality. In-degree centrality being the number of incoming connections a member has and out-degree centrality being the number of outgoing connections a member has. A member with a high out-degree could be defined as influential as they would have influenced a decent amount of members. While, members with high in-degree centrality would likely have a high susceptibility score as they are susceptible to the influence of many members.

In *Tables 3 & 4* the results for running the graph measures statistics on the CONTROL and ACTIVE LEADER Experiment are shown. *Table 3* shows that out of all the iterations run on the CONTROL experiment, m00 was found as the most influential by betweenness centrality, closeness centrality, and hub link analysis. While m01 was found as the most influential by page rank link analysis and authorities link analysis. *Table 4* shows that out of all the iterations run on the ACTIVE LEADER experiment, c00_m00 was found the most influential by all graph measures except Authorities link analysis in which c00_m01 was found the most influential for.

Table 3: The community member identified as the most influential at the end of the CONTROL experiment using Centrality and Link Analysis algorithms.

Graph Measure	Betweenness Centrality	Closeness Centrality	PageRank Link Analysis	Hubs Link Analysis	Authorities Link Analysis
Member ID	c00_m00	c00_m00	c00_m01	c00_m00	c00_m01
Member Type	Leader	Leader	Leader	Leader	Leader

Table 4: The community member identified as the most influential at the end of the ACTIVE LEADER experiment using Centrality and Link Analysis algorithms.

Graph Measure	Betweenness Centrality	Closeness Centrality	PageRank Link	Hubs Link Analysis	Authorities Link Analysis
Member ID	c00_m00	c00_m00	c00_m00	c00_m00	c00_m01

Member Type	Leader	Leader	Leader	Leader	Leader

The in, out, and total degree centrality for the members in the CONTROL and ACTIVE LEADER experiments can be found in *Tables 5 & 6* respectively. The CONTROL and ACTIVE LEADER experiment both list m00 as the top member in terms of the out-degree measures. m01 was listed as the highest in-degree measure for the CONTROL experiment and m00 was listed as the highest in-degree measure for the ACTIVE LEADER experiment. In both experiments the total degree number was the highest for member m00.

Table 5: Degree Centrality measures for the non-Luker community members in the CONTROL experiment.

Member ID	Member Type	In-degree	Out-degree	Total Degree
c00_m00	Leader	571	784	1355
c00_m01	Leader	619	665	1284
c00_m02	Participant	77	93	170
c00_m03	Participant	95	102	197
c00_m04	Participant	73	93	166
c00_m05	Participant	69	113	182
c00_m06	Participant	83	104	187
c00_m07	Participant	82	105	187
c00_m08	Participant	70	92	162
c00_m09	Participant	87	80	167
c00_m10	Participant	73	86	159
c00_m11	Participant	99	72	171
c00_m12	Participant	95	99	194
c00_m13	Participant	81	103	184
c00_m14	Participant	95	103	198
c00_m15	Participant	80	96	176
c00_m16	Participant	72	90	162

Member ID	Member Type	In-degree	Out-degree	Total Degree
c00_m17	Participant	65	88	153
c00_m18	Participant	64	76	140
c00_m19	Participant	108	54	162

Table 6: Degree Centrality measures for the non-Luker community members in the ACTIVE LEADER experiment.

Member ID	Member Type	In-degree	Out-degree	Total Degree
c00_m00	Leader	1181	863	2044
c00_m01	Leader	1137	772	1909
c00_m02	Participant	80	119	199
c00_m03	Participant	106	119	225
c00_m04	Participant	48	137	185
c00_m05	Participant	80	135	215
c00_m06	Participant	93	142	235
c00_m07	Participant	81	139	220
c00_m08	Participant	100	144	244
c00_m09	Participant	89	130	219
c00_m10	Participant	75	129	204
c00_m11	Participant	100	126	226
c00_m12	Participant	97	123	220
c00_m13	Participant	81	136	217
c00_m14	Participant	110	111	221
c00_m15	Participant	91	116	207
c00_m16	Participant	85	136	221
c00_m17	Participant	74	116	190
c00_m18	Participant	86	147	233

Member ID	Member Type	In-degree	Out-degree	Total Degree
c00_m19	Participant	129	71	200

If we compute the probability of each member being influential instead of identifying only the most influential member, we get the results shown in *Figures 11 & 12*. These figures show two groupings of algorithms. The first group is the collection of the Centrality and Link Analysis algorithms. The second group is the results of the Influence Score measurements. The graphs show that the probability density functions across the algorithms have similar shapes. That is, they compute a positive probability of being influential for the Leader and Participant member types (c00_m00 through c00_m19) and a zero probability of being influential for Lurker member types (c00_m19 through c00_m199). These figures also show some variation among these algorithms, *e.g.*, the Betweenness Centrality algorithm computes the highest probability of being influential for the Leader member. For both experiments, the influence score and Betweenness Centrality algorithms drop significantly within the first two members, while the other measures stay at a higher value until reaching the Lurker members. It should also be noted that the difference between the influence likelihood in the CONTROL experiment and the ACTIVE LEADER experiment is minimal.

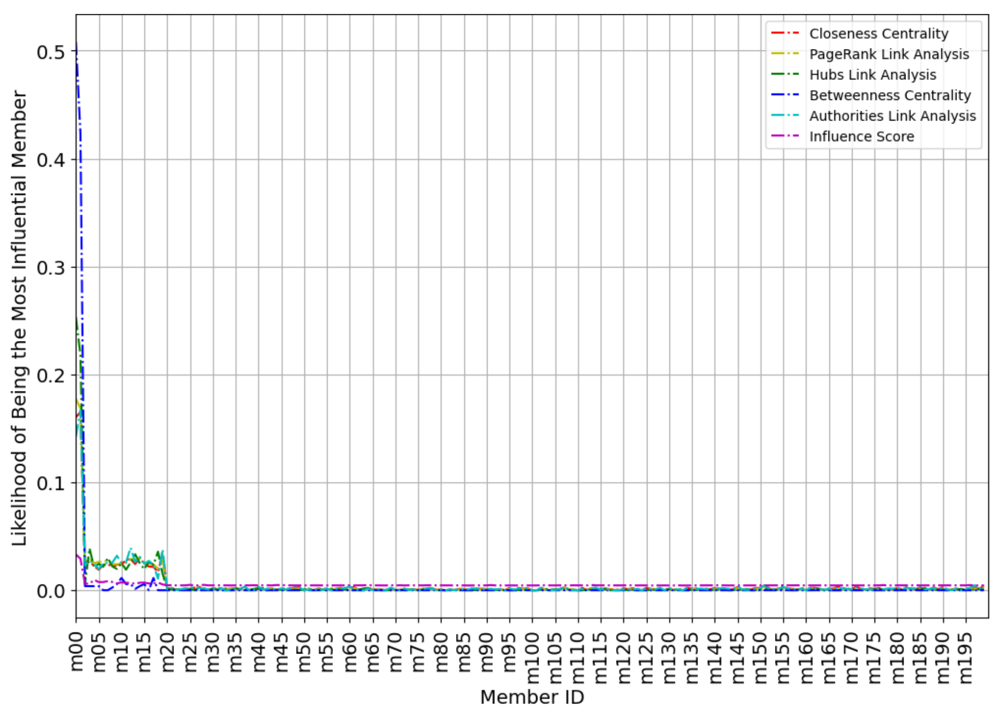

Figure 11: Likelihood of being influential for each member in the CONTROL experiment.

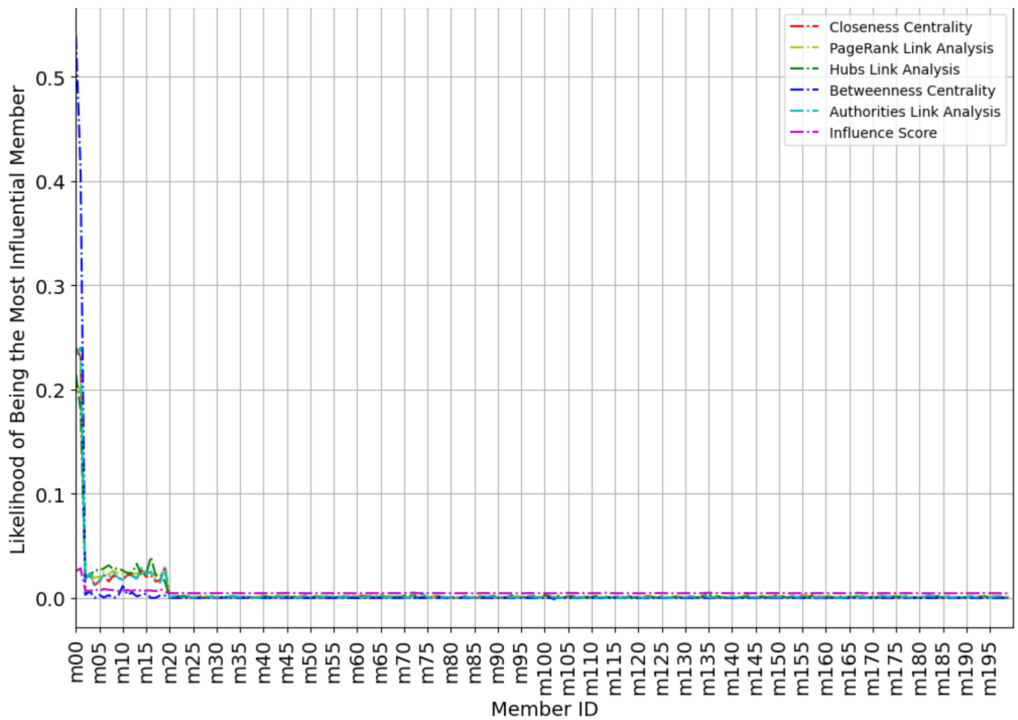

Figure 12: Likelihood of being influential for each member in the ACTIVE LEADER experiment.

Both *Figures 13 & 14* show that the Leader members (m00 and m01) have the highest likelihood of being the most influential members for Closeness Centrality, Pagerank Link Analysis, Hubs Link Analysis, Betweenness Centrality, Authorities Link Analysis, and Influence Score for both the CONTROL and ACTIVE LEADER experiment. The Betweenness Centrality has the highest difference between the Leaders and non-Leaders likelihood centrality. Four of the algorithms (Closeness Centrality, PageRank Link Analysis, Hubs Link Analysis, Authorities Link Analysis) show a probability that features two members (c00_m00 and c00_m01) being at least 80% more likely to be influential than the Participant members. The Betweenness Centrality algorithm exhibited distributions where the Leaders are at least 95% more likely to be influential than the Participant members.

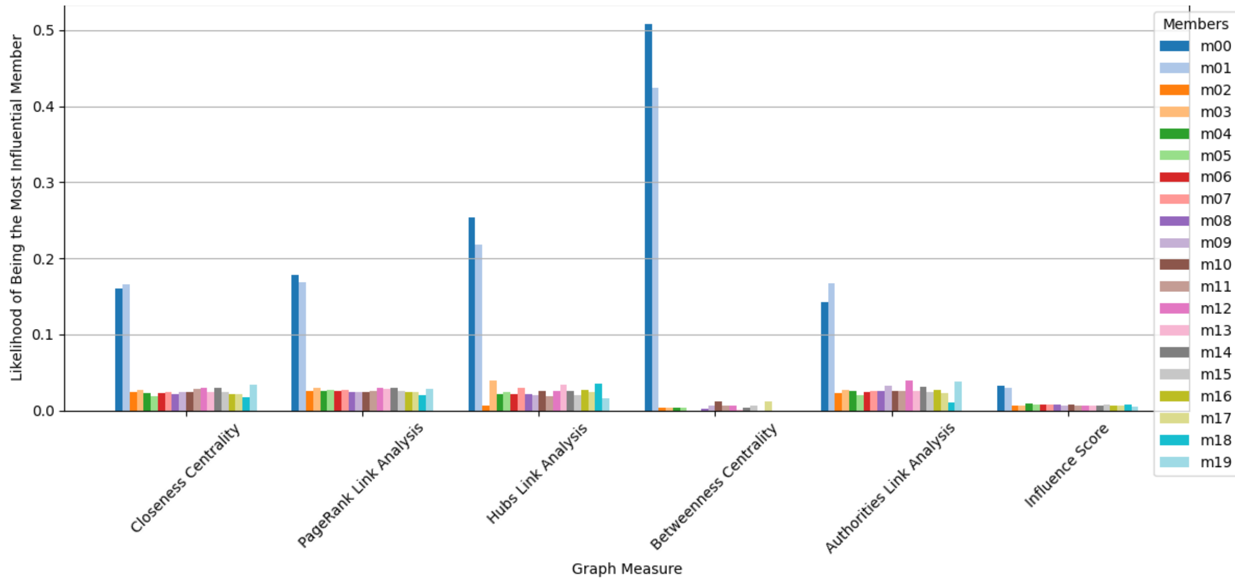

Figure 13: Likelihood of being influential for non-Lurker members in the CONTROL experiment.

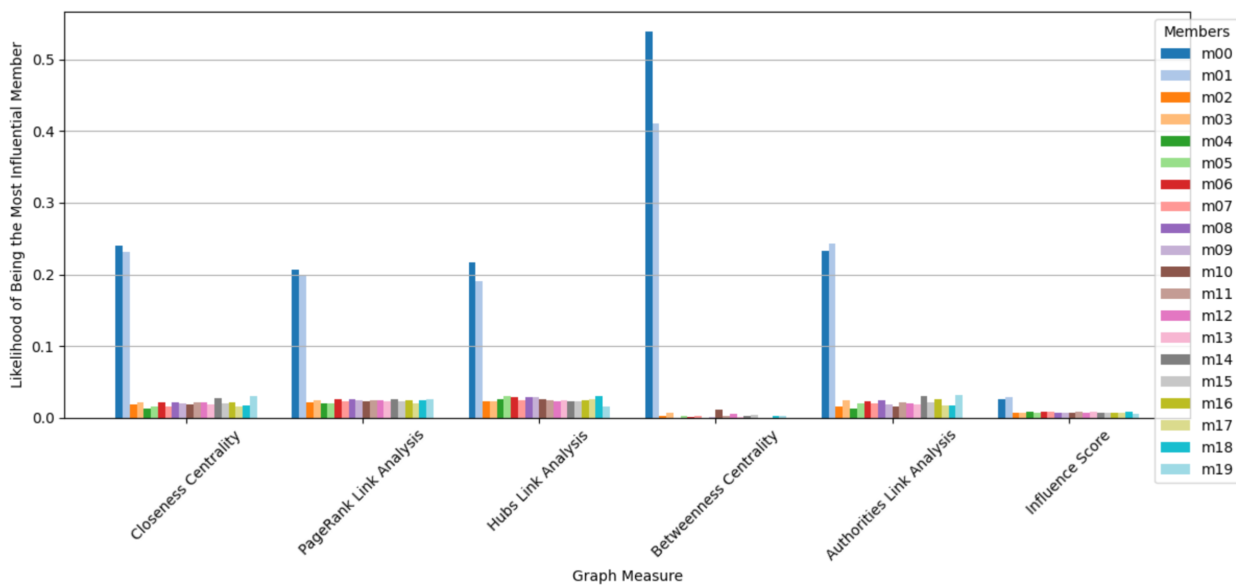

Figure 14: Likelihood of being influential for non-Lurker members in the ACTIVE LEADER experiment.

In *Tables 7 & 8*, the results for running a Kolmogorov-Smirnov test between each graph measure algorithm and influence algorithm is shown. This test was run to understand if there is a significant difference between the measures used to compute influence. In both the CONTROL and the ACTIVE LEADER experiment the results show that the probability distributions for the graph measures are different from the probability distributions for the influence score.

Table 7: Results of Kolmogorov-Smirnov tests to compare the distributions of the probability of influence between the Centrality and Link Analysis algorithms to the Influence Score algorithm for the CONTROL Experiment.

Algorithm	Critical Value (α=0.05)	D(100,100)	Result
Closeness Centrality	0.0962	0.5778	Reject
PageRank Link Analysis	0.0962	0.6262	Reject
Hubs Link Analysis	0.0962	0.7176	Reject
Betweenness Centrality	0.0962	0.8694	Reject
Authorities Link Analysis	0.0962	0.5771	Reject

Table 8: Results of Kolmogorov-Smirnov tests to compare the distributions of the probability of influence between the Centrality and Link Analysis algorithms to the Influence Score algorithm for the ACTIVE LEADER Experiment.

Algorithm	Critical Value (α=0.05)	D(100,100)	Result
Closeness Centrality	0.0962	0.6446	Reject
PageRank Link Analysis	0.0962	0.6402	Reject
Hubs Link Analysis	0.0962	0.6673	Reject
Betweenness Centrality	0.0962	0.8964	Reject
Authorities Link Analysis	0.0962	0.5176	Reject

Interestingly, the Leaders were not only the most influential members but also the most susceptible to influence. To quantify susceptibility, we measured the number of iterations in which a member exhibited the highest number of stance changes. The member with the most stance changes in a given iteration was labeled the most susceptible for that round. As shown in *Table 9*, during the CONTROL experiment, Leader c00_m00 was identified as the most susceptible in 58 iterations, and c00_m01 in 51 iterations, while all other members were the most susceptible in three or fewer iterations. In the ACTIVE LEADER experiment (*Figure 10*), this pattern became even more pronounced: the Leaders were the only members ever labeled as the most susceptible, with c00_m00 and c00_m01 being the most susceptible in 61 and 60 iterations respectively. No other members were identified as most susceptible in any iteration. These results suggest that increased activity and exposure to opposing viewpoints—as seen in the ACTIVE LEADER condition—may simultaneously increase both influence and susceptibility.

Table 9: Most Susceptible Members by Number of Iterations for the CONTROL Experiment.

Member ID	Member Type	Iterations Identified as Most Susceptible
m01	Leader	58
m00	Leader	51
m12	Participant	3
m02	Participant	2
m08	Participant	2
m15	Participant	1
m06	Participant	1
m117	Lurker	1
m130	Lurker	1
m154	Lurker	1
m155	Lurker	1
m16	Participant	1
m26	Lurker	1
m07	Participant	1
m05	Participant	1

Member ID	Member Type	Iterations Identified as Most Susceptible
m14	Participant	1
m11	Participant	1

Table 10: Most Susceptible Members by Number of Iterations for the ACTIVE LEADER Experiment.

Member ID	Member Type	Iterations Identified as Most Susceptible
m01	Leader	61
m00	Leader	60

To estimate the likelihood that a given member was the most susceptible to influence, we calculated each member's proportion of total stance changes across all conversation turns and simulation iterations. For each iteration, we summed the number of stance changes per member, normalized it by the total number of stance changes across all members to compute a probability density function (PDF), and then aggregated these PDFs across all runs. The final susceptibility likelihood for each member was obtained by normalizing their cumulative PDF, yielding a probability distribution that reflects how consistently a member exhibited susceptibility to influence. *Figure 15* illustrates this distribution for non-Lurker members in the CONTROL experiment, where the two Leader members (c00_m00 and c00_m01) stand out as the most susceptible. As shown in *Figures 15 & 16*, the ACTIVE LEADER experiment results in even higher susceptibility likelihoods for the Leaders, with the highest reaching 0.30 compared to 0.25 in the CONTROL experiment. This increase is likely driven by the presence of the Heterophily cognitive bias in the ACTIVE LEADER condition, which causes Leaders to engage more frequently with opposing viewpoints, thereby increasing the probability of a stance change.

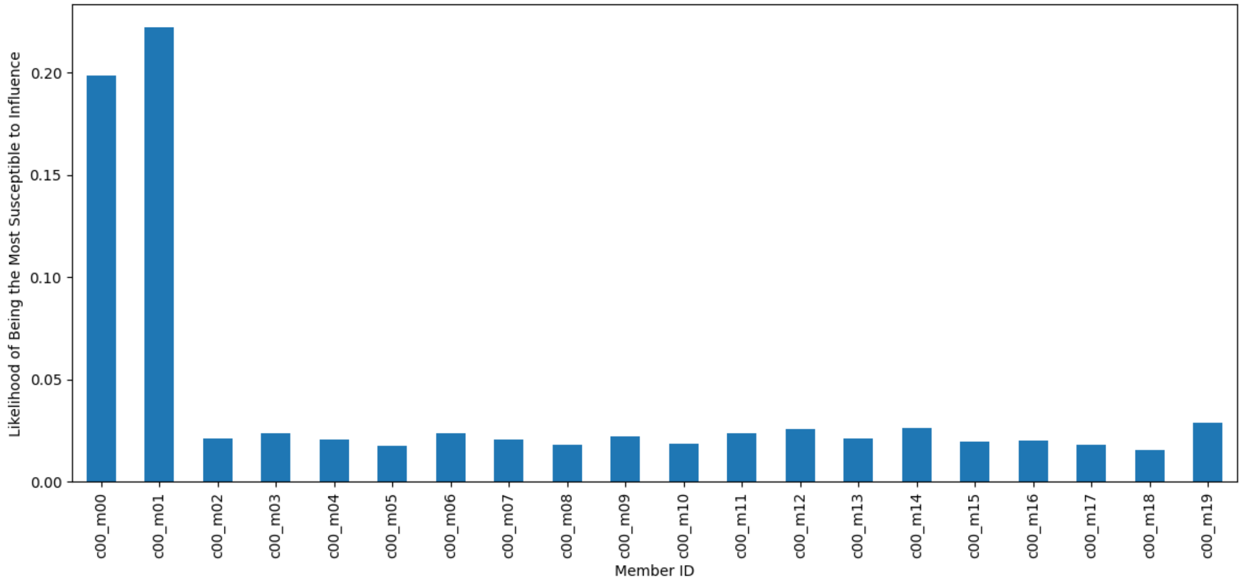

Figure 15: Likelihood of the member being susceptible to influence in the CONTROL experiment for non-Lurker members.

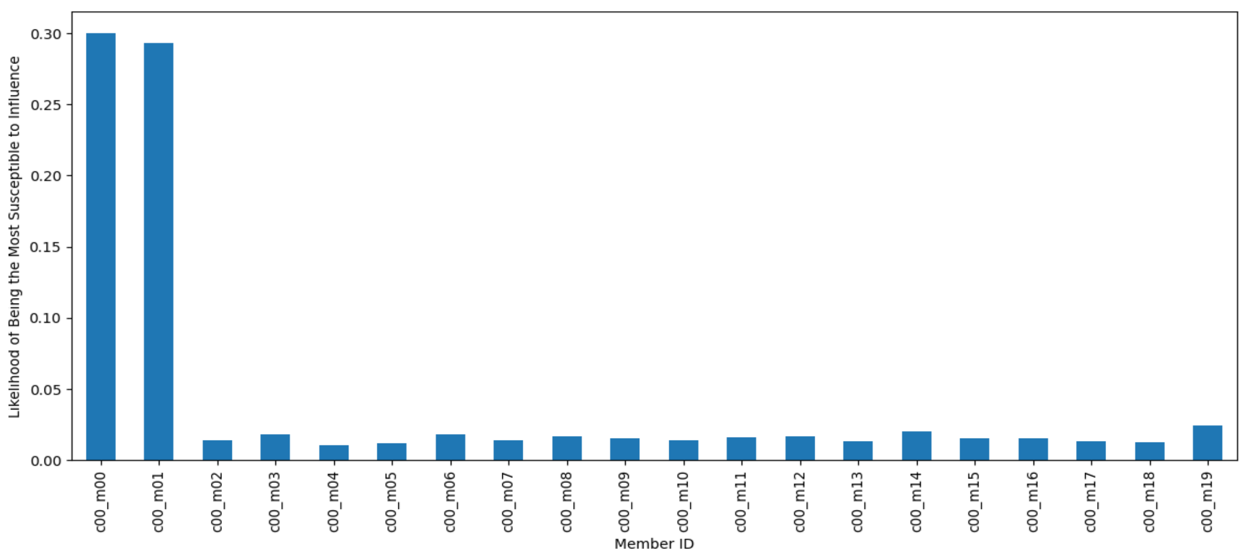

Figure 16: Likelihood of the member being susceptible to influence in the ACTIVE LEADER experiment for non-Lurker members.

4.2 Comparing Influence Dynamics: Blog Communities vs. One-to-One Dialogues

RQ2: What differences exist between the distribution of the ability to influence in a text-based online blog community and one-to-one dialogue between community members?

Along with comparing the results from the CONTROL experiment to the ACTIVE LEADER experiment, the results of the online community blog model are also compared to the one-to-one dialogue community. In this section, we compare the influence metrics between these two communities to understand the difference in how influence moves and is distributed between members in both communities. As seen in *Table 11* there are similarities between the graph measures for the one-to-one dialogue community and online blog community. In both models the Leader c00_m00 is the top member for the following graph measures: Betweenness Centrality, Closeness Centrality, and Hubs Link Analysis. However, in both models the graph measures PageRank Link analysis and Authorities Link analysis list a Participant as the member for the one-to-one digilogue community and the Leader c00_m01 for the online blog community.

Table 11: The community member identified as the most influential at the end of the CONTROL experiment using Centrality and Link Analysis algorithms for the one-to-one dialogue model.

Graph Measure	**Betweenness Centrality**	**Closeness Centrality**	**PageRank Link Analysis**	**Hubs Link Analysis**	**Authorities Link Analysis**
Member ID	c00_m00	c00_m00	c00_m06	c00_m00	c00_m05
Member Type	Leader	Leader	Participant	Leader	Participant

Figures 17 & 18 show results for the likelihood of being the most influential in the CONTROL experiment of the one-to-one dialogue private model. When comparing the likelihood of being the most influential member between both models, there are similarities seen in the Betweenness Centrality metric. In both models the Betweenness Centrality is higher for the Leaders by a difference that is larger than any other measurement. Also, in both models' influence score is lower than any other measure for all of the members. In terms of differences, the Leaders in the CONTROL experiment for the online blog community consistently always have the highest likelihood of being the most influential while all of the other non-Lurker members are lower. However, in the one-to-one dialogue community, the Leader only takes the lead in Hubs Link analysis and Betweenness Centrality. Also, overall the likelihood probability is very uneven in terms of the distribution amongst the members for the online blog community.

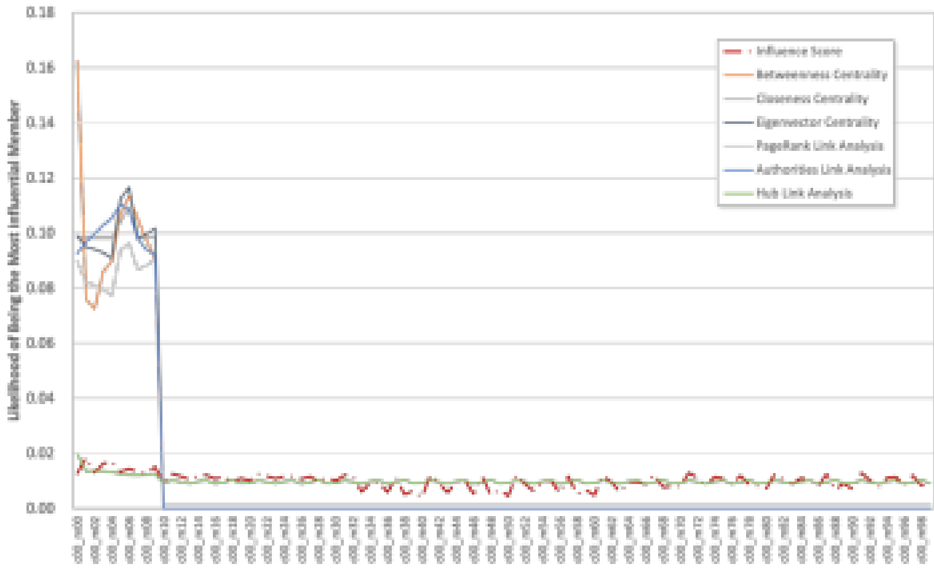

Figure 17: Likelihood of being influential for each member in the CONTROL experiment.

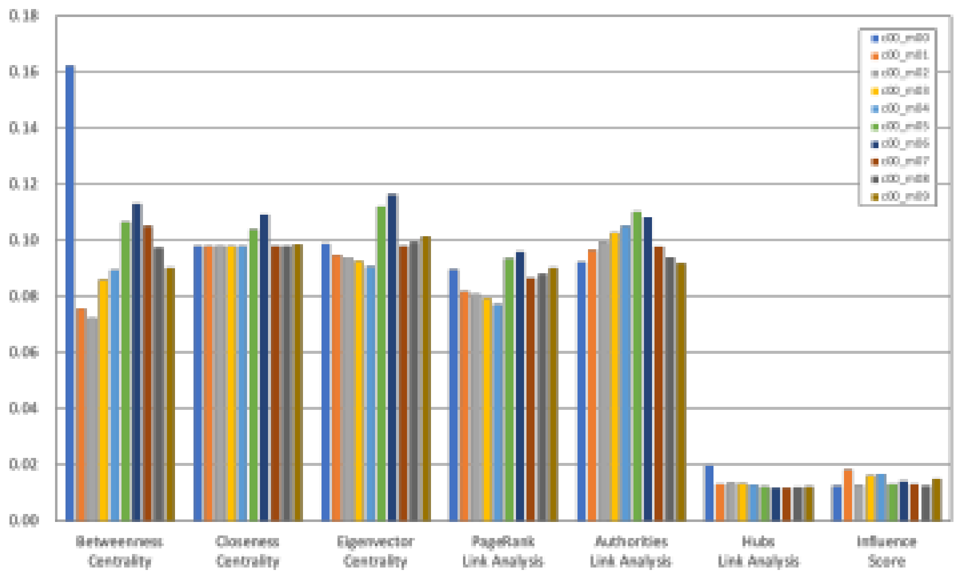

Figure 18: Likelihood of being influential in the CONTROL experiment for non-Lurker members in one-to-one dialogue community.

4.3 Comparing Susceptibility to Influence: Blog Communities vs. One-to-One Dialogues

RQ3: What differences exist between the distribution of the susceptibility to influence in a text-based online blog community and one-to-one dialogue between community members?

Like the public model, the private model measured the likelihood of being the most susceptible to influence among non-Lurker members based on their one-to-one dialogue interactions. In this section, we compare susceptibility outcomes between the private model's dyadic interaction structure and the public model's blog-style community structure within the CONTROL experiment. As shown in *Figure 19*, in the private model, Participant members hold the highest likelihood for susceptibility, whereas in the public model, Leader members hold the highest likelihood. Results from the private model indicate that Participant members exhibit the highest likelihood of being the most susceptible, with two members in particular—c00_m01 and c00_m03—standing out. Notably, the Leader member does not rank among the most susceptible in the private model, although it does have a non-zero likelihood of susceptibility—equal to that of the least susceptible Participant, c00_m06. All Participant members (c00_m01 to c00_m09) display susceptibility probabilities equal to or exceeding that of the Leader, whose likelihood is only 0.16. In contrast, the public model reveals a markedly different pattern: Leader members dominate in susceptibility, with probabilities at least eight times greater than those of the most susceptible Participants, as illustrated in *Figure 15*.

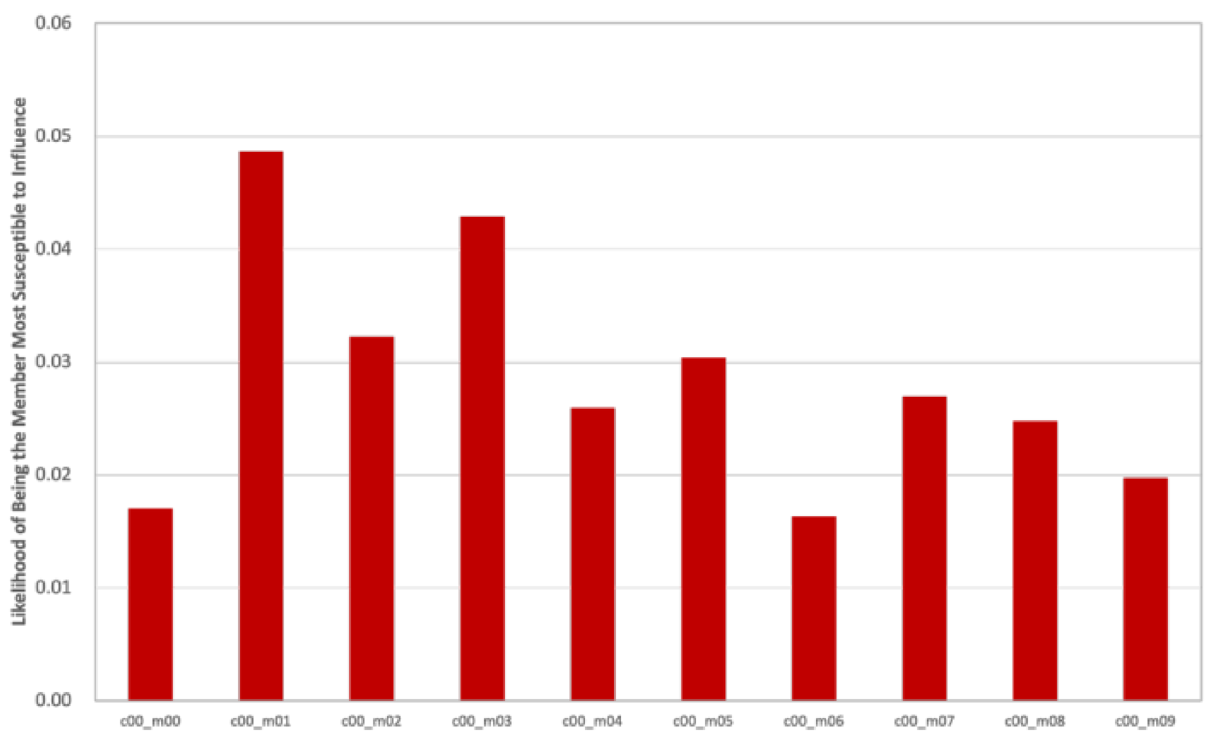

Figure 19: Likelihood of the member being susceptible to influence in the CONTROL experiment for non-Lurker members in the private model.

Moreover, susceptibility among Participant members shows a wider range in the private model compared to the public model, where the variation is more limited. In the private model, as illustrated in *Figure 20*, the Participant with the highest likelihood of susceptibility has a value of 0.049, while the lowest is 0.016—a difference of 0.033. In contrast, the public model, shown in *Figure 16*, exhibits a narrower spread: the highest likelihood among Participants is 0.025, and the lowest is 0.015, resulting in a much smaller difference of just 0.01. This suggests that the one-to-one dialogue structure of the private model may lead to greater differentiation in susceptibility across individual Participants, whereas the blog-style format of the public model produces a more uniform distribution. Lastly, all Lurker members in the private model were assigned a constant probability of susceptibility, which was approximately 3.6 times lower than the average probability for non-Lurkers. In contrast, the public model did not apply a constant probability for Lurkers; instead, their susceptibility likelihoods varied, though clustered near zero.

5 Discussion

5.1 Modeling Influence and Susceptibility in Blog Communities

Leaders were consistently identified as the most influential members across all influence metrics, including raw influence score statistics and NetworkX-based graph measures. Interestingly, Leaders were also found to be the most susceptible to influence. This is likely due to their elevated activity levels—specifically, their frequent posting and commenting throughout the experiments. As shown in *Figure 22,* during the CONTROL experiment, Leaders were responsible for 53.48% of all posts and comments, while Participants contributed 33.28%, and Lurkers only 1.81%. Similarly, in the ACTIVE LEADER experiment (*Figure 25*), Leaders created 53.05% of the content, Participants 33.54%, and Lurkers a mere 0.15%. *Figures 20, 21, 23, & 24* show bar charts displaying Leaders' dominance in creating both posts and comments. This dominant content generation by Leaders provides them with more opportunities to influence others, as other members are often responding to and changing their stance from Leader-generated content. Regarding susceptibility, the same frequent engagement likely increases Leaders' exposure to differing viewpoints, which in turn raises the probability of stance changes, leading to a higher number of stance changes compared to other members. Thus, their high activity not only amplifies their influence but also renders them more susceptible to influence from others in the community.

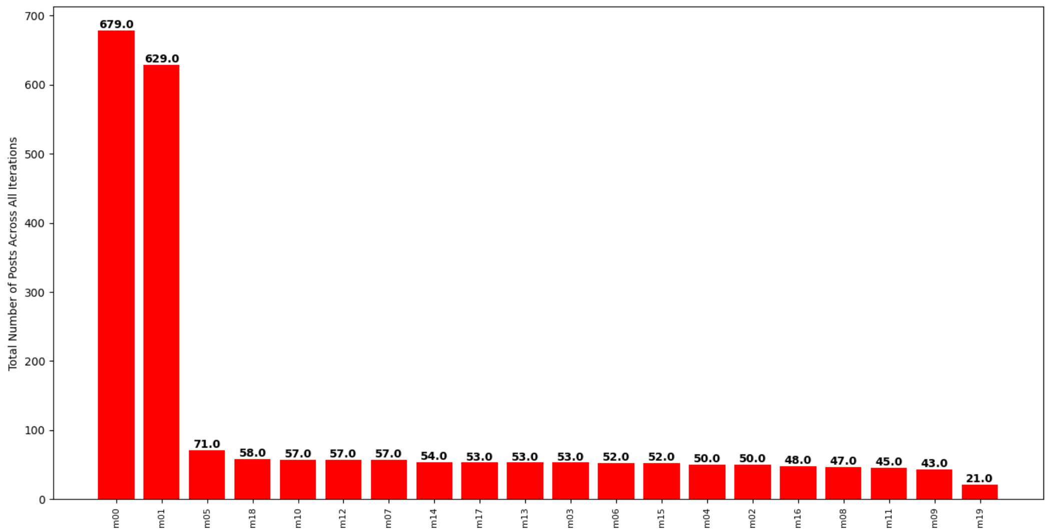

Figure 20: Total posts across all iterations for all non-Lurker members in the CONTROL experiment.

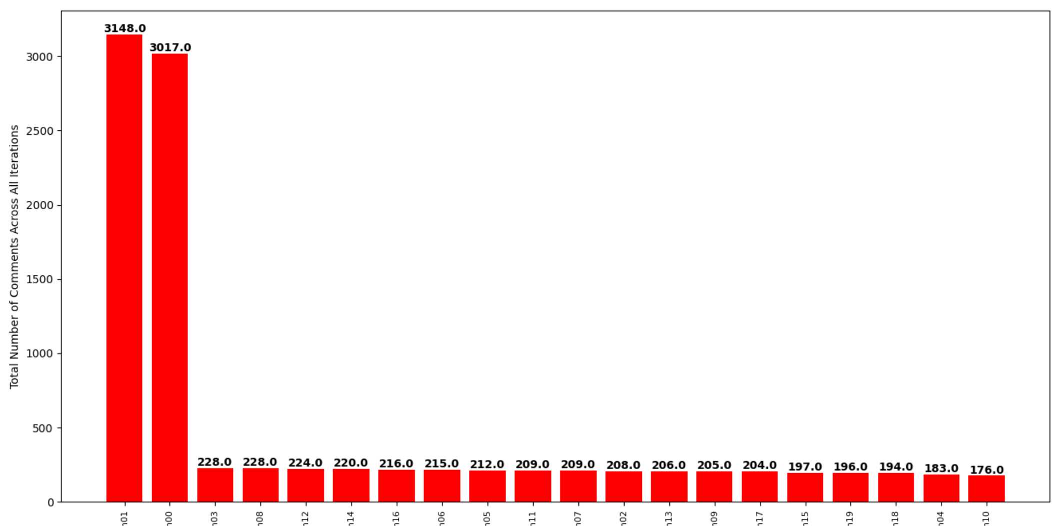

Figure 21: Total comments across all iterations for all non-Lurker members in the CONTROL experiment.

```
Total Posts:  2253
Total Comments:  11721
Proportion of Comments to Posts:  5.2024
Proportion of Posts + Comments that are Leaders:  0.5348
Proportion of Posts + Comments that are Participants:  0.3328
Proportion of Posts + Comments that are Lurkers:  0.0181
```

Figure 22: Distribution of posts and comments for all members in the CONTROL experiment.

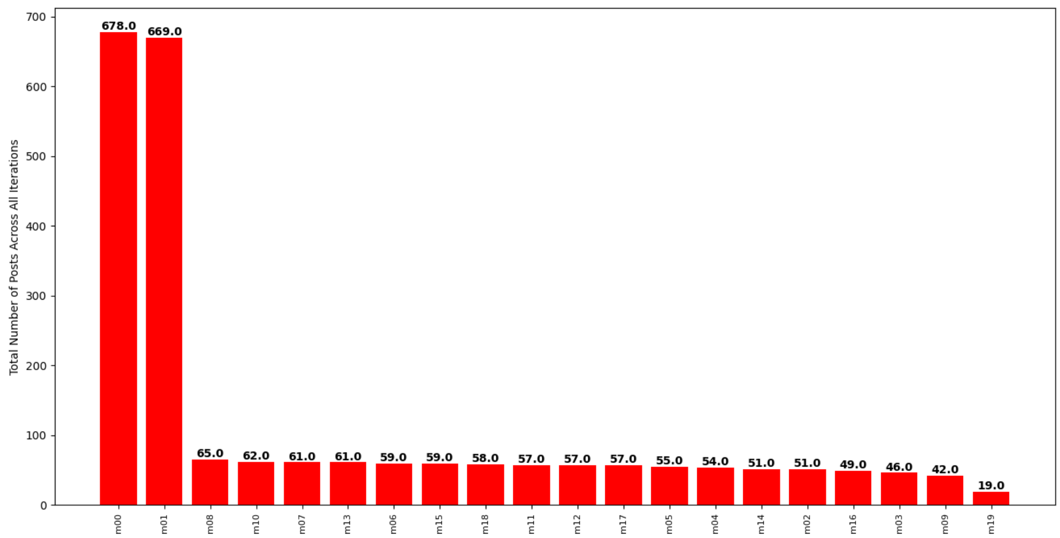

Figure 23: Total posts across all iterations for all non-Lurker members in the ACTIVE LEADER experiment.

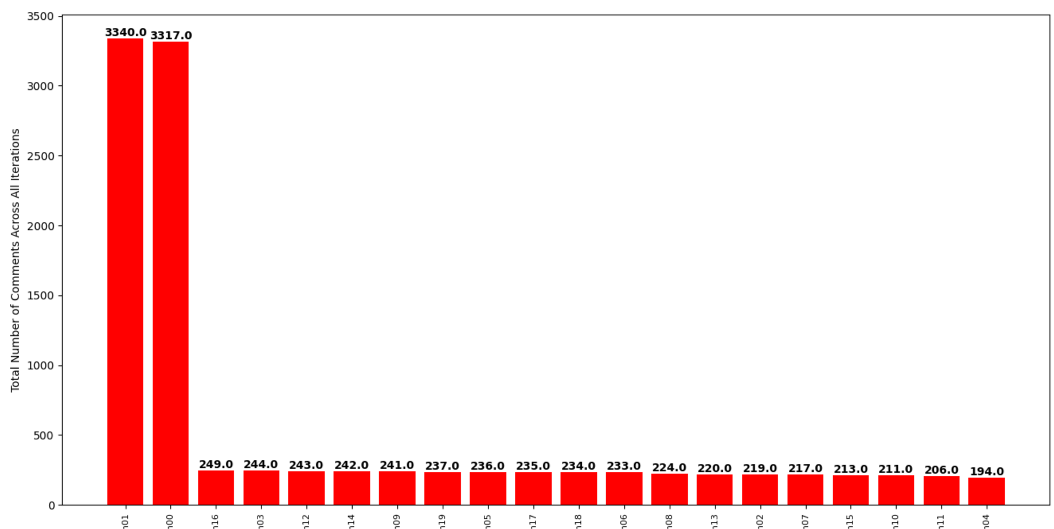

Figure 24: Total comments across all iterations for all non-Lurker members in the ACTIVE LEADER experiment.

```
Total Posts:  2328
Total Comments:  12761
Proportion of Comments to Posts:  5.4815
Proportion of Posts + Comments that are Leaders:  0.5305
Proportion of Posts + Comments that are Participants:  0.3354
Proportion of Posts + Comments that are Lurkers:  0.015
```

Figure 25: Distribution of posts and comments for all members in the ACTIVE LEADER experiment.

5.2 Comparing Influence Dynamics: Blog Communities vs. One-to-One Dialogues

The results for the CONTROL experiment for both the online blog community and one-to-one dialogue are analyzed in this section to get an understanding of the difference in influence between a public community and a private community.

The graph analytics for the public and private conversation model highlighted the variance in the two models in how they measure influence and how members interact in both. The private and public conversation model followed a similar pattern of having the same Leader rank the highest in terms of being influential by Betweenness Centrality, Closeness Centrality, and Hubs Link Analysis. Authorities Link Analysis and PageRank Link Analysis had a different member for both models being defined as the most influential. This similarity potentially brings up the questions of why the members that are deemed influential with the previously mentioned graph analytics are not doing the same for PageRank and Authorities Link Analysis. Both of these measurements define the "important" sources of information in a community. Are the members who are discussing the most information not also deemed as the "important" sources of information? This topic could potentially explore the difference between spam and content with substance and how to distinguish between the two. The public and private model may potentially be at risk to spam being defined as influence in a community with the aforementioned results.

The difference in the Degree metrics between the public and private conversation model were clear. While the Leaders were defined as the most influential in both models by their out-degree and total degree, the range in the degree metrics was wider in the public model than in the private model. This may be the result of not spreading out activity across the members in a more even way. The Leaders overwhelmingly dominate conversations in the public model while conversations are distributed more evenly in the private model. There are more opportunities for Participants and Lurkers to discuss information with their one-hop neighbors compared to posting/commenting in the public conversation model.

Lastly, when looking into the likelihood of each member being influential, the private conversation model has a more even spread amongst members while the public conversation model designates the majority of the likelihood percentage to the top two Leaders. This result could be due to the idea that in the public conversation model there are two Leaders so they will take up more of the conversation. These results could also suggest that since the Leaders dominate conversations in the public conversation model they will also have a higher chance of being defined as the most influential member. In the private conversation model, members talk to their 1-hop neighbors and these neighbors could include Lurkers, Leaders, or Participants. In the public conversation model, the members choose who they would like to interact with based on the post and comments that they see. If the majority of the comments and posts are authored by Leaders then they will mainly be interacting with Leaders. These results show that being a Leader in a public conversation model gives more opportunity to gain likelihood in being the most influential. In a private conversation model, there is a higher potential for Participants to become the most influential member.

5.3 Comparing Susceptibility to Influence: Blog Communities vs. One-to-One Dialogues

There is a significant difference in susceptibility to influence between the private model's one-to-one dialogues and the public model's blog-style community interactions. The private model identifies Participants as the most susceptible to influence, whereas the public model consistently finds Leaders to by far the most susceptible. Moreover, susceptibility exhibits greater variation among Participants in the private model, while in the public model, variation among Participants is minimal and tightly clustered.

In the private model, one-to-one interactions ensure that each member engages directly and repeatedly with others, promoting more balanced exposure to differing viewpoints. Participants, in particular, may be influenced more in this setting because they are not overshadowed by highly active Leaders, allowing their stances to shift more frequently through dyadic exchanges. As a result, susceptibility in the private model is more evenly distributed across both Participant and Leader members, with several Participants exhibiting the highest likelihood of being influenced.

Conversely, in the public model, Leaders dominate the discourse by generating the majority of posts and comments. This heightened activity not only amplifies their influence but also increases their exposure to opposing viewpoints—especially when cognitive biases like Heterophily are present, as in the ACTIVE LEADER experiment. This bias causes Leaders to engage more frequently with content that contradicts their stance, making them more likely to undergo stance changes. Consequently, in the public model, susceptibility becomes highly concentrated among Leaders, with Participants and

Lurkers contributing minimally. These findings suggest that the structure of communication—whether distributed through private dialogues or centralized through public threads—plays a crucial role in shaping who is influenced and how that influence spreads through the community.

Additionally, susceptibility displays a greater range between highly and minimally susceptible members in the private model, while the public model demonstrates a more compressed distribution—particularly among Participants. This broader range in the private model likely arises from its interaction structure, which gives each Participant more opportunities to engage and be influenced based on individual conversational dynamics. In contrast, the hierarchical nature of the public model—where members often respond to high-visibility Leader content—restricts opportunities for lower-activity Participant members to meaningfully participate or be influenced, thus flattening variation to smaller likelihoods. These differences highlight the importance of interaction context and communication architecture in determining both who is influenced and the variability of that influence within a community.

5.4 Limitations

There are several limitations in our study that future work could address. First, our experiments used a fixed community composition of 180 Lurkers, 18 Participants, and 2 Leaders. While this adheres to the commonly observed 90:9:1 participation rule in online communities, it may not generalize to communities with different member distributions. Future research could explore how varying these proportions affects influence and susceptibility outcomes. Second, our current susceptibility metric considers only whether a member's stance changed, not the magnitude of that change. For instance, a minor shift from PRO-HIGH to PRO-MID is treated equivalently to a major reversal from PRO-HIGH to CON-HIGH. In practice, greater changes may reflect higher susceptibility, suggesting that future models should incorporate stance change magnitude into susceptibility scoring, just as we already do for influence. Furthermore, our simulations were limited to communities of 200 members. While this size allows for controlled experimentation, it may not fully capture the complexity of large-scale platforms like Reddit, which host millions of active users. Scaling up future simulations could help validate the findings in more realistic, large-scale environments. Lastly, the public model included twice as many members as the private model—200 versus 100—in order to accommodate two Leader members who could interact in large volumes with each other through comments and posts. However, this difference in community size limits the direct comparability of results between the public and private models, as the scale of interaction and opportunities for influence may differ significantly.

6 Conclusion

This work set out to quantify influence and susceptibility among members of a blog-style online community, modeled after platforms like Reddit using a post-and-comment structure. To achieve this, we extended the original A3G private model—which simulated one-to-one interactions—by introducing a tree-structured framework of posts and comments, resulting in the A3G public model. In addition, we developed a novel metric to quantify influence in the public model, which assigns weighted influence scores to different members based on their relationship to the individual whose stance changed.

We then compared patterns of influence and susceptibility between the private and public models. Our findings show that the likelihood of being the most influential member in the public conversation model favored the Leaders more often than in the private conversation model. They also show that in the private model, Participant members had the highest likelihood of being the most susceptible to influence, whereas in the public model, susceptibility was heavily concentrated among Leader members. This divergence is likely due to structural differences between the models: the private model allows Participants to engage directly and more evenly with their 1-hop neighbors through one-to-one interactions, while the public model is dominated by Leader-driven discourse, limiting exposure opportunities for less active members. These results underscore the importance of communication structure in shaping influence dynamics within online communities.

7 References

Agarwal, N., Liu, H., Tang, L. et al. Modeling blogger influence in a community. Soc. Netw. Anal. Min. 2, 139–162 (2012). https://doi.org/10.1007/s13278-011-0039-3.

Akar, E., & Mardikyan, S. (2018). User Roles and Contribution Patterns in Online Communities: A Managerial Perspective. SAGE Open, 8(3). https://doi.org/10.1177/2158244018794773 (Original work published 2018).

Giovanidis, Anastasios, Bruno Baynat, Clemence Magnien, and Antoine Vendeville. 2021. "Ranking Online Social Users by Their Influence." IEEE/ACM Transactions on Networking 29 (5): 2198–2214. https://doi.org/10.1109/TNET.2021.3085201.

Humphrey Mensah, Lu Xiao, and Sucheta Soundarajan. 2019. Characterizing Susceptible Users on Reddit's ChangeMyView. In Proceedings of the 10th International Conference on Social

Media and Society (SMSociety '19). Association for Computing Machinery, New York, NY, USA, 102–107. https://doi.org/10.1145/3328529.3328550.

Radakovid, Milos. (2010). "The Origins: Where Is the Connection between Persuasion and Rhetoric?" Accessed April 29, 2025. https://www.diplomacy.edu/resource/the-origins-where-is-the-connection-between-persuasion-and-rhetoric/.

Flaugher, Jonathan, and Tamar Haviv. “Reddit's 2020 Year in Review - Upvoted.” Reddit, 8 December 2020, https://redditinc.com/blog/reddits-2020-year-in-review. Accessed 19 April 2025.

Kien-Weng Tan, L., Na, J. and Theng, Y. (2011), "Influence detection between blog posts through blog features, content analysis, and community identity", Online Information Review, Vol. 35 No. 3, pp. 425-442. https://doi.org/10.1108/14684521111151450.

Sun, Na, Patrick Pei-Luen Rau, and Liang Ma. “Understanding Lurkers in Online Communities: A Literature Review.” Computers in Human Behavior, vol. 38, 2014, pp. 110–117. Elsevier, https://doi.org/10.1016/j.chb.2014.05.022.

Guadagno, R., Cialdini, R.: Online Persuasion and Compliance: Social Influence on the Internet and beyond. In: Amichai-Hamburger, Y. (ed.) The social net: The social psychology of the Internet. pp. 91–113. New York: Oxford University Press (2007).

Williams, Emma J., Amy Beardmore, and Adam N. Joinson. 2017. “Individual Differences in Susceptibility to Online Influence: A Theoretical Review.” Computers in Human Behavior 72: 412–421. https://doi.org/10.1016/j.chb.2017.03.002.

Xiong, Zhengli, Wenjun Jiang, and Guojun Wang. “Evaluating User Community Influence in Online Social Networks.” In 2012 IEEE 11th International Conference on Trust, Security and Privacy in Computing and Communications, 640–47, 2012. https://doi.org/10.1109/TrustCom.2012.152.